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Distributed Incremental Least Mean-Square for Parameter Estimation using Heterogeneous Adaptive Networks in Unreliable Measurements

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Abstract
Adaptive networks include a set of nodes with adaptation and learning abilities for modeling various types of self-organized and complex activities encountered in the real world. This paper presents the effect of heterogeneously distributed incremental least mean-square (LMS) algorithm with ideal links on the quality of unknown parameter estimation. In heterogeneous adaptive networks, a fraction of the nodes, defined based on previously calculated signal-to-noise ratio (SNR), is assumed to be the informed nodes that collect data and perform in-network processing, while the remaining nodes are assumed to be uninformed and only participate in the processing tasks. As our simulation results show, the proposed algorithm not only considerably improves the performance of the Distributed Incremental LMS algorithm in the same conditions but also proves a good accuracy of estimation in cases where some of the nodes make unreliable observations (noisy nodes). Also studied is the application of the same algorithm on the cases where node failure happens.

Keywords: *Adaptive Networks, Distributed Estimation, Least Mean-Square (LMS), Informed Nodes, Mean Square Deviation (MSD).*

1. Introduction

Wireless sensor networks (WSNs) consist of a large number of sensor nodes and a base station. The nodes in a wireless sensor network are usually arranged randomly inside the region of interest. The base station is engaged to give commands to all the sensor nodes and collect data from them. A sensor node is a tiny device that includes three essential components: a sensing sub-system for data acquisition from the physical surrounding environment, a processing sub-system for local data processing and storage, and a wireless communication sub-system for data transmission. In many WSN applications, the final goal is to get an exact estimate of an unknown parameter based on the temporal data obtained by spatially distributed sensors [1-4]. This estimation problem can be solved by either a centralized approach (with fusion center) or a decentralized one [5]. In many applications, however, sensors need to make estimation in a constantly changing environment without having available a statistical model for the underlying processes of interest [6]. This issue motivated the development of distributed adaptive estimation algorithms or adaptive networks. An adaptive network is a set of adaptive nodes that observe space–time data and work together, according to some cooperation protocols, in order to estimate a parameter [7–14]. Also in [15], they could manage the resource problem embracing the adaptive control of the input and output traffic flows by coping with the random fluctuations of the input traffic to be processed and the states of the utilized TCP/IP connections. From an application viewpoint, it guarantees, by design, reliable transport of data and also allows the vehicular client to perform flow control in order to adaptively match the transmission rate of the serving Road Side Unit (RSU) to the actual (time-varying) operating conditions of the mobile device used.

Propagation and hybrid, which are composed of back-propagation learning algorithm and least square method, are regarded as two learning methods generally used in adaptive neuro-fuzzy inference system (ANFIS) models to specify the relationship between input and output and to determine optimized distribution of membership functions [16]. Also in [17], the authors have developed an ANFIS-based model to estimate the wind turbine power coefficient in a wind farm. The results achieved clearly indicate that the proposed ANFIS model is efficient to provide accurate estimations.

Depending on the manner by which the nodes communicate with each other, they may be referred to as incremental algorithms or diffusion algorithms. In the former, a cyclic path through the network is required, and nodes communicate with neighbours within this path. In the latter, nodes communicate with all of their neighbours, and no cyclic path is required. Recently, several algorithms have been developed to make use of this nature of the sensor nodes, and cooperation schemes have been formalized to improve estimation in sensor networks. Various algorithms have been proposed to allow each node share information locally with its neighbours and to estimate parameters using the information; these include incremental least mean squares (LMS) [8], diffusion LMS [13,18], diffusion RLS [9], and diffusion Kalman filtering [19]. The LMS algorithms are a class of adaptive filters used to imitate a desired filter by finding the filter coefficients that are related to the generation of the least mean squares of the error signal (i.e. the difference between the desired and the actual signal) [20]. The incremental solution suffers from a number of limitations for applications involving adaptation and learning from streaming data [21]. First, the incremental strategy is sensitive to the agent or link failures. If an agent or link over the cyclic path fails, then the information flow over the network is interrupted. Second, starting from an arbitrary topology, determining a cyclic path that visits all agents is generally an NP-hard problem. Third, cooperation between agents is limited to each agent allowed to receive data from one preceding agent and to share data with one successor agent. In contrast, the incremental-based networks present excellent estimation performance, particularly in small size networks, while diffusion based networks are more robust to link and node failures. In most previous works [8, 13, 18], the nodes in the network have been assumed to be homogeneous in that all nodes had similar capabilities and were able to have continuous access to measurements.

The authors in [22] have designed a distributed and adaptive resource management controller, which facilitates the optimal use of cognitive radio and soft-input/soft-output data fusion in vehicular access networks. In this case, multiple car smartphones equipped with heterogeneous cognitive capabilities and energy approximations play the role of secondary users and contend to request the serving Road Side Units (RSUs) by opportunistically accessing the time and frequency holes of the traffic flow generated by the primary user of the Internet backbone (Service Provider). This ultimately results in the joint maximization of the aggregate access throughput of the entire network, and the average per-client access rates. Also in [23], they used WSN design, as a multi-objective optimization problem through Genetic Algorithm (GA) technique and showed in all the network situations, random deployment has better performance compared to grid deployment.

In addition, it is often observed in biological networks that the behaviour of the network tends to be dictated more heavily by a small fraction of the agents, as happens with bees and fish. This observation is the motivation to study what we shall refer to as heterogeneous adaptive networks [24, 25], where a fraction of the nodes, according to the estimation of observation noise of nodes, are assumed to be informed, while the remaining nodes are taken as uninformed. We study the performance of a heterogeneous network on distributed incremental LMS algorithm according to a defined threshold, and also simulate a network with noisy nodes. Then we will show that the proposed network works better in overcoming the degradation problem due to noisy nodes, and is robust to observation quality of the nodes. The simulation results show the effectiveness of our proposed algorithm.

This article is organized as what follows. The problem of distributed parameter estimation and incremental solution are explained in Section 2. In Section 3, the proposed method for identifying informed and uninformed nodes with respect to defined SNR are discussed. Subsequently, Section 4 shows the simulation results and the effect of number of these nodes and their distribution for accuracy of estimation. Finally, conclusions are provided in Section 5.

Notation: Throughout the paper, we use boldface letters for random quantities. The * symbol is used for both complex conjugation of scalars and Hermitian transpose.

2. Distributed estimation problem

We considered a connected network consisting of N nodes. Each node k collects scalar measurements $\mathbf{d}_k(i)$ and $1 \times M$ regression data vectors $\mathbf{u}_{k,i}$ over successive time instants with a positive definite covariance matrix , $R_{u,k} = E\boldsymbol{u}^*_{k,i}\boldsymbol{u}_{k,i}$. Two nodes are said to be neighbors if they can share information. The set of neighbors of node *k* including k itself is called the neighborhood of *k*, and is denoted by N_k. The measurements across all nodes are assumed to be related to a set of unknown M × 1 vectors $\{w^o\}$ via a linear regression model of the form [20]:

$$\boldsymbol{d}_k(i) = \boldsymbol{u}_{k,i} w^0 + \boldsymbol{v}_k(i), \quad k = 1, 2, ..., N \tag{1}$$

where, $\mathbf{v}_k(i)$ means measurement or model noise with variance $\sigma^2_{v,k}$, and assumed to be spatially and temporally white, i.e.

$$E\boldsymbol{v}^*_k(i)\boldsymbol{v}_l(j) = \sigma^2_{v,k}.\delta_{kl}.\delta_{ij} \tag{2}$$

in terms of the Kronecker delta function. The noise $\mathbf{v}_k(i)$ is also assumed to be independent from $\mathbf{u}_{l,j}$ for all l and j. All random processes are assumed to be zero mean, and w^o denotes the parameter of interest for node *k*. For example, w^o can be the parameter vector of some underlying physical phenomenon, the location of a food source or a vector modeling different groupings of nodes. The nodes in the network would like to estimate the vectors $\{w^o\}$ by seeking the solution for the following minimization problem:

$$J^{Globe}(w) = \sum_{k=1}^{N} E\left|\boldsymbol{d}_k(i) - \boldsymbol{u}_{k,i} w\right|^2 \tag{3}$$

In most previous works, a common value for all vectors was assumed so that all nodes across the network were following the same unknown parameter. The solution to (3) (i.e. w^o) is given by:

$$\begin{cases} w^0 = R_u^{-1} R_{du}, \\ R_{du} = \sum_{k=1}^{N} E[\boldsymbol{d}_k(i)\boldsymbol{u}^*_{k,i}], R_u = \sum_{k=1}^{N} E[\boldsymbol{u}^*_{k,i}\boldsymbol{u}^*_{k,i}] \end{cases} \tag{4}$$

In order to use (4), each node must have access to the global statistical information $\{R_u, R_{du}\}$ that in many applications are not available or change in time. However, in situations where a multitude of nodes has access to data, and assuming that some form of collaboration is allowed among the nodes, it is more useful to seek solutions that can take advantage of node cooperation. In addition, since the statistical profile of the data may vary with time and space, it is useful to explore cooperative strategies that are inherently adaptive. For example, the noise and signal-to-noise (SNR) conditions at the nodes may vary in time and space as well as the model parameters themselves. Under such conditions, it is helpful to endow the network of nodes with learning abilities so that it can function as an adaptive entity in its own right. By doing so, one would end up with an adaptive network, where all nodes respond to data in real-time through local and cooperative processing, as well, adapt to variations in the statistical properties of the data [7].

2.1. Incremental solution

To address this issue and moreover, to enable the network to respond to changes in statistical properties of data in real time, the incremental LMS adaptive network is proposed in [8]. The update equation for incremental LMS is given by:

$$\begin{cases} \psi_0^i \leftarrow w_{i-1} \\ \psi_k^i = \psi_{k-1}^i + \mu_k \boldsymbol{u}^*_{k,i}[\boldsymbol{d}_k(i) - \boldsymbol{u}_{k,i}\psi_{k-1}^i] \\ w_i \leftarrow \psi_N^i \end{cases} \tag{5}$$

where, ψ_k^i denotes the local estimate of w^o at node k at time i, and μ_k is the step size. In the incremental LMS algorithm, the calculated estimates (i.e. ψ_k^i) are sequentially circulated from node to node, as shown in figure 1.

$$\psi_k^{(i)} = \psi_{k-1}^{(i)} + \mu_k \boldsymbol{u}^*_{k,i}[\mathbf{d}_k(\mathrm{i}) - \boldsymbol{u}_{k,i}\psi_{k-1}^{(i)}]$$

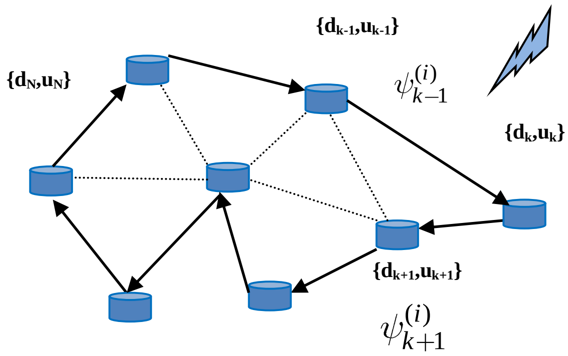

Figure 1. Structure of incremental LMS adaptive network.

A good measure of the adaptive network performance is the steady-state mean-square deviation (MSD), which for each node k is defined as follows:

$$\eta_k \triangleq E(\left\|\tilde{\psi}_{k-1}^{(\infty)}\right\|^2) \tag{6}$$

where

$$\tilde{\psi}_{k-1}^{(i)} \triangleq w^o - \psi_{k-1}^{(i)} \tag{7}$$

The mean-square performance of incremental LMS algorithm is studied in [20] using energy conservation arguments. The analysis relies on the linear model (1) and the following assumptions:

(i) {$\mathbf{u}_{k,i}$} are spatially and temporally independent.

(ii) The regressors {$\mathbf{u}_{k,i}$} arise from a circular Gaussian distribution with covariance matrix $R_{u,k}$.

In [8], a complex closed-form expression for MSD has been derived. However, in the case of small step sizes, simplified expressions for the MSD can be described as follows:
For each node k, introduce the eigen decomposition $R_{u,k} = T_k \Lambda_k T_k^*$, where T_k is unitary, and Λ_k is a diagonal matrix of the eigenvalues of $R_{u,k}$ as follow:

$$\Lambda_k = diag\{\lambda_{k,1}, \lambda_{k,2}, ..., \lambda_{k,M}\} \tag{8}$$

Then according to the results from [7,8]:

$$\eta_k \approx \frac{1}{2}\sum_{j=1}^{M}\left(\frac{\sum_{l=1}^{N}\mu_l^2\sigma_{v,l}^2\lambda_{l,j}}{\sum_{l=1}^{N}\mu_l\lambda_{l,j}}\right) \tag{9}$$

3. Proposed algorithm

We examined the performance of heterogeneous network in distributed incremental LMS algorithm. Thus we considered two types of agents: informed and uninformed. Informed agents receive new data regularly and perform consultation and in-network processing tasks, while uninformed agents participate solely in the consultation tasks. The criterion for choosing informed and uninformed node is as follows:

$$\mu_k = \begin{cases} \mu & for\ SNR\ of\ node\ k > Threshold \\ 0 & for\ SNR\ of\ node\ k < Threshold \end{cases} \tag{10}$$

If step size μ_k satisfies the condition that for every informed node, $0 < \mu.\rho(R_u) < 2$, where $\rho(.)$ denotes the spectral radius, where

$$Threshold = 10\log(mean(\frac{\mathrm{E}\left|\mathbf{u}_{k,i}\right|^2}{\sigma_{v,k}^2})) \tag{11}$$

In fact, for each node, we compute SNR, the threshold without the mean operator, and compare it to each node of the network. If any node gets more than this threshold, we assign a step size μ for it, which otherwise is an uninformed node and the assigned step size is zero. Thus SNR at node k (or equivalently, the observation quality) is inversely proportional to the observation noise variance [26, 27]. The mean stability analysis aims to find out the sufficient conditions such that the local estimate at each node converges in the mean to the unknown parameter w^o.

3.1. Mean stability

Let the error vector for any node k be $\tilde{\psi}_k^i = w^0 - \psi_k^i$.

We collected all weight error vectors and step-sizes across the network into a block vector and M = diag $\{\mu_k I_M\}$. Then starting from (7) and using model (1), we can verify that the weight error vector evolves according to the relation below:

$$\tilde{\psi}_k^i = [I - MR_i]\tilde{\psi}_{k-1}^i - M\boldsymbol{u}_{k,i}^* v_k(i) \tag{12}$$

where

$$R_i = diag\{\boldsymbol{u}_{k,i}^*\boldsymbol{u}_{k,i}\} \tag{13}$$

With assumption (i), whic implies $\boldsymbol{u}_{k,i}$ is independent from $\tilde{\psi}_{k-1}^i$ and taking expectation value of both sides of (12), we find that the mean relation of $\tilde{\psi}_k^i$ evolves in time according to the recursion:

$$E\tilde{\psi}_k^i = [I - MR_i]E[\tilde{\psi}_{k-1}^i] - ME[\mathbf{u}_{k,i}^* v_k(i)] \tag{14}$$

$$E\tilde{\psi}_k = \begin{cases} [I - MR]E[\tilde{\psi}_{k-1}], \text{ informed node} \\ I\ E[\tilde{\psi}_{k-1}], \text{ uninformed node} \end{cases} \tag{15}$$

Thus if we have at least one informed node, the mean stability even in the presence of uninformed nodes is guaranteed.
Also in a practical sensor network, a sensor may be damaged or attacked, making its measurement unreliable, and does not have any information about w^0. If this happens, the sensor will only observe the pure noise and certainly degrade the estimation performance [28]. We refer to this phenomenon as node failure mode or low-quality nodes [28]. This is simulated by data model (16).

$$\boldsymbol{d}_k(i) = \begin{cases} \boldsymbol{u}_{k,i} w^0 + \boldsymbol{v}_k(i) & \text{usual node} \\ \boldsymbol{v}_k(i) & \text{failure node} \end{cases} \tag{16}$$

4. Simulation results

In order to show the homogenous and heterogeneous adaptive network performance, we present a simulation example in figures 2-11. Figures 2-4 show the network topology with N = 10 nodes (four nodes are informed), seeking an unknown filter with M = 5 taps, along with the network statistical profile. The regressors are zero-mean Gaussian, independent from time and space, with covariance matrices $R_{u,k}$. The background noise power is denoted by $\sigma_{v,k}^2$. Figure 5 shows the transient performance for the incremental LMS algorithm (6) using a uniform μ = 0.01. The results are averaged over 50 experiments. We also compared the network MSD of the proposed algorithm (heterogeneous) with that of the conventional (homogenous) incremental LMS algorithm in figure 5. At the initial state, the proposed algorithm showed slow convergence rate unlike the conventional algorithm that uses a constant step size for all nodes. As iteration continued, it converged a steady state with low steady-state error, which is better than the conventional algorithm. The SNR (dB) of each node (red) and threshold (blue) of network are shown in figure 6.

As shown, the number of informed nodes with this configuration of the network is four. Also we simulated this method for a variety of step sizes. As shown in figure 7, this method works better for different step sizes.

To see the effect of noisier nodes, we again considered a network with N = 10 nodes but with different statistical profile for nodes. One of the nodes belongs to (0, 3), and the other nodes belong to (0, 0.02). Simulations of this condition are shown in figures 8 and 9.

As it is shown, the proposed method works considerably better than the usual incremental algorithm for both informed and uninformed noisier nodes. The reason for this improvement is that when any of the nodes gets noisier than others, the proposed algorithm assigns step size zero for it and the remaining nodes cooperate in the update stage. See the threshold curves in figures 8 and 9.

Regarding the other condition, in a realistic sensor network, a sensor may be damaged or attacked, making its measurement unreliable. If this happens, the sensor will only observe the pure noise (modeled by its observation noise) and degrade the estimation performance. We refer to this event as node failure.

As shown in figures 10 and 11, when the node failure happens, this method again works better than the homogeneous network if the failed node belongs to uninformed nodes. However, this is not the case for the informed nodes.

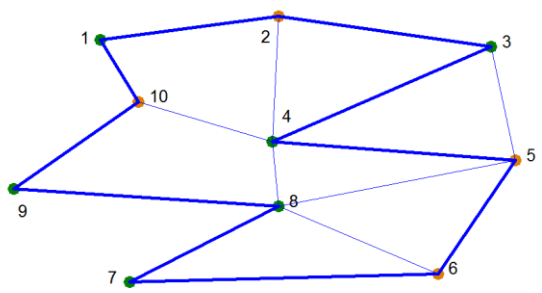

Figure 2. Network topology for N = 10 nodes (red nodes are informed).

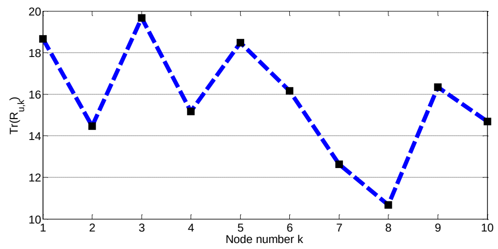

Figure 3. Trace of regressor covariances Tr($R_{u,k}$).

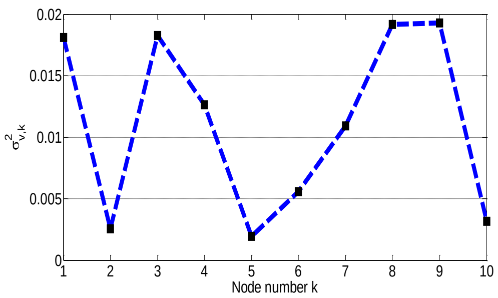

Figure 4. noise variances $\sigma^2_{v,k}$.

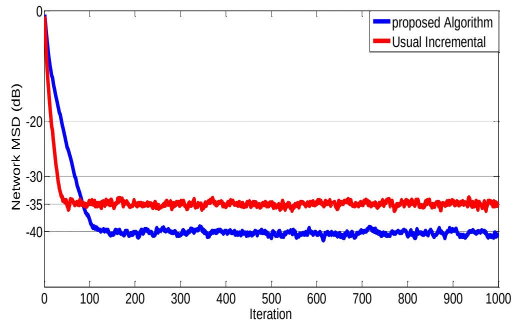

Figure 5. Transient network MSD for usual (red) and proposed (blue) incremental LMS.

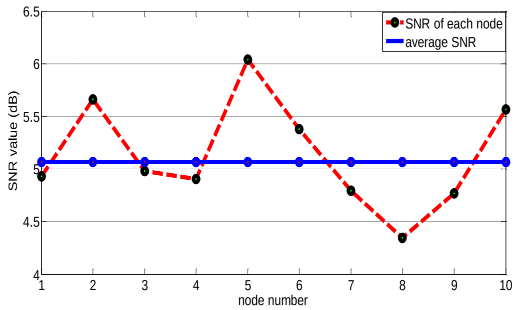

Figure 6. SNR of each node (red) and threshold (blue) of network.

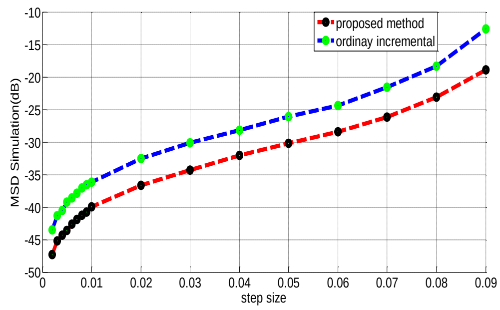

Figure 7. MSD differences for a variety of step sizes (4 nodes are informed).

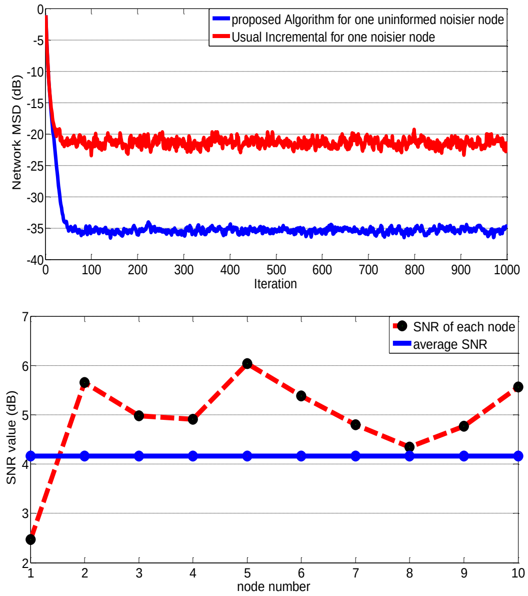

Figure 8. Transient network MSD for usual (red) and proposed (blue) incremental LMS for first uninformed noisier node (top) and new network design (bottom).

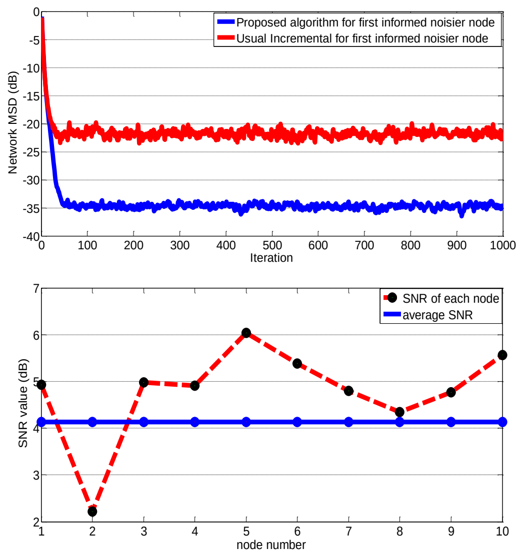

Figure 9. Transient network MSD for usual (red) and proposed (blue) incremental LMS for first informed noisier node (top) and new network design (bottom).

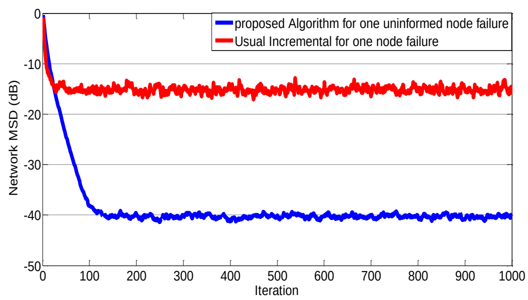

Figure 10. Transient network MSD for usual (red) and proposed (blue) incremental LMS for first uninformed node failure.

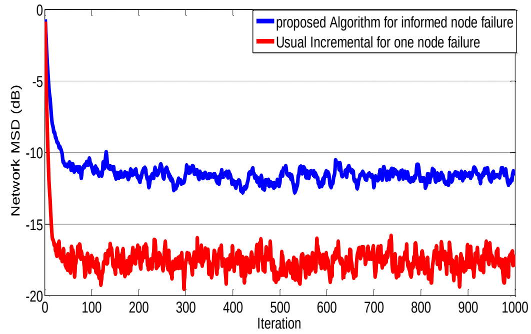

Figure 11. Transient network MSD for usual (red) and proposed (blue) incremental LMS for first informed node failure.

5. Conclusions

In this paper, we considered various conditions of informed and uninformed nodes in distributed incremental adaptive estimation problem with ideal links. By defining a threshold and assigning node labels, we showed that the performance of the network with this configuration was better than the usual distributed incremental LMS (DILMS) algorithm. Then we examined this proposed method in a network containing some noisier nodes, and, as our simulation results showed, the proposed algorithm considerably improved the performance of the DILMS algorithm in the noisy condition. Also when the node failure happens, if the failed node belongs to uninformed nodes, this method again works better than homogeneous network, unlike informed nodes. On the other hand, since by increasing the number of informed nodes the performance of the network gets closer to homogeneous networks, if we locate the informed nodes in some safer places against failure, this kind of method would work better in all unreliable conditions. Extension of this work to noisy links is the subject of the future communications.

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نشریه هوش مصنوعی و داده کاوی

اثر شبکه ناهمگون تطبیقی افزایشی برپایه کمترین مربعات خطا برای تخمین پارامتر ناشناخته در مشاهدات نامطمئن

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چکیده:

شبکه‌های تطبیقی، گره‌های با قابلیت یادگیری و تطبیق هستند که برای مدل کردن رفتارهای پیچیده در جهان واقعی بکار می‌روند. این مقاله بـه تـاثیر شبکه‌های ناهمگون افزایشی برپایه الگوریتم کمترین مربعات خطای توزیع شده بر کیفیت پارامتر تخمین ناشناخته با لینک‌هـای ایـده‌ال مـی‌پـردازد. در شبکه‌های ناهمگون، تعدادی از گره‌ها بر اساس نسبت سیگنال به نویز مطلع تعریف خواهند شد که هم در کار جمع‌آوری اطلاعات و هـم پـردازش درون شبکه‌ای هستند درحالی‌که بقیه گره‌ها وظیفه آپدیت نداشته و نامطلع خوانده می‌شوند. همچنان‌که شبیه‌سازی‌ها نشان می‌دهند، الگوریتم پیشنهادی نـه تنها باعث بهبود نتیجه تخمین نهایی شبکه می‌گردد بلکه در محیطی که کیفیت مشاهدات گره‌ها با گذشت زمان کاهش می‌یابد از افـت تخمـین شـبکه جلوگیری می‌کند. همچنین در مورد خرابی این گره‌ها در ادامه بحث و شبیه‌سازی صورت گرفته است.

کلمات کلیدی: شبکه‌های تطبیقی، تخمین توزیع‌شده، کمترین مربعات خطا، گره‌های مطلع، میانگین مربعات خطا.